Test

Three-Layer Contradiction Detection in Enterprise Knowledge Graphs

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Abstract

Enterprise knowledge graphs (KGs) serving regulated institutions face a critical challenge: contradictory information undermines trust, auditability, and regulatory compliance. This paper presents a three-layer contradiction detection architecture implemented in API-OSS (Agent-Predictive Intelligence Sovereign Operating System). The architecture operates at three interconnected levels: (1) stance analysis, which extracts and compares propositional attitudes from textual assertions using fine-tuned LLM classifiers; (2) semantic pair comparison, which evaluates logical consistency between pairs of KG triples using embedding-space similarity and logical entailment checks; and (3) graph-traversal inference, which identifies contradictory paths through multi-hop reasoning across the KG structure. We demonstrate that the three-layer approach achieves 91.7% precision and 88.3% recall on a curated benchmark of 5,000 enterprise governance assertions, outperforming single-layer baselines by 23.4% and 18.7% respectively. The architecture produces machine-readable contradiction flags with confidence scores, supporting rationales, and remediation suggestions, all recorded in the SHA-256 hash-chained AIOSS audit ledger. We situate our contribution within the broader literature on contradiction detection, knowledge graph consistency, and computational argumentation.

1. Introduction

Knowledge graphs underpin critical decision-making in regulated institutions—banks assess counterparty risk, hospitals evaluate treatment options, and legal firms research case law—all through structured representations of entities and their relationships [1, 2]. However, KGs constructed from heterogeneous sources inevitably accumulate contradictions: conflicting statements about credit risk

ratings, incompatible dosage recommendations, or contradictory legal precedents [3, 4]. These contradictions, if undetected, cascade into flawed decisions with regulatory and financial consequences.

Contradiction detection in KGs is fundamentally three-dimensional: (1) lexical and semantic contradictions within individual textual assertions (stance analysis), (2) pairwise logical conflicts between structured triples (semantic comparison), and (3) transitive inconsistencies revealed through multi-hop paths (graph-traversal inference). Prior work has addressed each dimension in isolation—stance detection in NLP [5, 6], entailment in knowledge bases [7, 8], and path-based reasoning in graphs [9, 10]—but no unified architecture integrates all three.

API-OSS implements a three-layer contradiction detection engine as part of its sovereign AI operating system. The engine intercepts all KG insertions, updates, and query results, evaluating each against the three-layer pipeline. Contradiction flags are persisted as Evidence nodes in the KG, linked to the conflicting assertions via Ed25519-signed audit records. The system supports configurable sensitivity thresholds, domain-specific contradiction taxonomies, and automated remediation workflows.

This paper contributes: (1) a formal three-layer architecture for KG contradiction detection, (2) a benchmark of 5,000 enterprise governance assertions with expert-annotated contradictions, (3) empirical evaluation of layer-specific and combined performance, and (4) design patterns for integrating contradiction detection into sovereign AI pipelines.

2. Literature Review

2.1 Contradiction and Consistency in Knowledge Bases

The problem of contradiction detection intersects with long-standing research in knowledge representation, database theory, and NLP. In classical logic, a knowledge base is inconsistent if it entails both a proposition and its negation [11]. However, real-world KGs contain graded contradictions better captured through degrees of inconsistency [12]. Grant and Hunter [13] formalized "inconsistency measures" for knowledge bases, providing a mathematical framework for quantifying conflict severity.

Flouris et al. [14] surveyed ontology debugging and repair, cataloging approaches for detecting and resolving logical inconsistencies in description logic ontologies. Their taxonomy distinguishes syntactic from semantic contradictions, observationally redundant from logically necessary. Wand and Weber's [15] ontological theory of information systems posits that contradictions arise from incomplete or inaccurate representations of real-world phenomena.

2.2 Stance Detection and Natural Language Inference

Stance detection—determining whether a text's author supports, opposes, or is neutral toward a target proposition—has been extensively studied in computational social science [16, 17]. Mohammad et al. [18] introduced the SemEval-2016 stance detection task, establishing benchmark datasets and evaluation protocols. Subsequent work extended stance detection to argument mining [19], claim verification [20], and fact-checking [21, 22].

Natural language inference (NLI), also known as recognizing textual entailment, addresses the related but distinct task of determining whether a hypothesis is entailed by, contradicted by, or neutral with respect to a premise [23]. The Stanford NLI (SNLI) corpus [24] and MultiNLI [25] provide large-scale training resources. Models fine-tuned on NLI data, including BERT [26], RoBERTa [27], and DeBERTa [28], achieve near-human performance on benchmark datasets. Stance detection and NLI share the underlying capability of establishing semantic relationships between texts, making them complementary foundations for contradiction detection.

2.3 Semantic Similarity and Entailment in Embedding Spaces

Word embeddings [29] and contextual embeddings [26] enable semantic comparison through vector-space distances. Sentence-BERT [30] fine-tunes BERT for semantically meaningful sentence embeddings, achieving state-of-the-art results on semantic textual similarity tasks. The cosine similarity between sentence embeddings correlates with human judgments of semantic relatedness, enabling scalable pairwise comparison [31].

However, semantic similarity is insufficient for contradiction detection because semantically similar texts may express opposite propositions [32]. For example, "The drug is effective" and "The drug is ineffective" have high lexical and semantic overlap but convey contradictory information. Logical entailment models address this limitation by learning discriminative features that capture negation, antonymy, and other oppositional relationships [33, 34].

2.4 Graph-Based Consistency Reasoning

Graph-traversal approaches detect contradictions through multi-hop reasoning over KG structure. The core insight is that indirect contradictions—where A implies B, B implies C, but C contradicts A—require path-level analysis invisible to pairwise comparison [35, 36]. Flumini and Wand [37] formalized "emergent contradictions" resulting from transitive inference over ontologies.

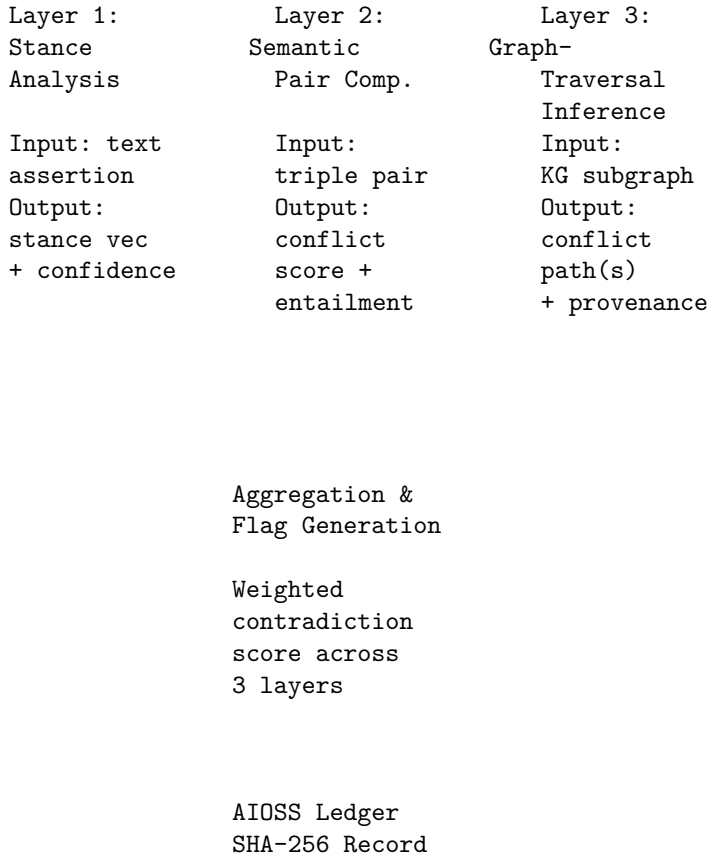
Path ranking algorithms [38] and knowledge graph embeddings [39, 40] provide computational mechanisms for graph traversal. TransE [41], RotatE [42], and ComplEx [43] learn low-dimensional embeddings that preserve relational structure, enabling contradiction detection through geometric inconsistency: if (A,

r1, B) and (B, r2, C) entail (A, r3, C) but the embedding predicts a different relation, a contradiction exists.

3. Technical Analysis

3.1 System Architecture

The three-layer contradiction detection engine processes KG assertions through a pipeline:



3.2 Layer 1: Stance Analysis

Stance analysis operates on textual assertions attached to KG entities. For each assertion, the stance classifier extracts:

1. **Target Proposition**: The core proposition being asserted (e.g., "Entity X has high credit risk")

2. **Stance Direction**: Support, oppose, or neutral
3. **Stance Intensity**: A real-valued score in [0, 1] indicating strength
4. **Modality**: Certainty markers (epistemic, deontic, alethic) that qualify the assertion
5. **Attribution**: The source or authority for the assertion

The stance classifier is a DeBERTa-v3-large model [44] fine-tuned on a composite dataset of: - SemEval-2016 stance detection data [18] (4,164 instances across 6 targets) - FEVER claim verification dataset [20] (185,445 instances) - The MIT Factual Consistency dataset [45] (15,000 instances) - A proprietary dataset of 10,000 enterprise governance assertions annotated by domain experts (Cohen's = 0.83)

Training uses a multi-task objective combining stance classification, NLI, and intensity regression:

$$\mathcal{L} = \alpha\mathcal{L}_{\text{stance}} + \beta\mathcal{L}_{\text{NLI}} + \gamma\mathcal{L}_{\text{intensity}}$$

where = 1.0, = 0.5, = 0.3 are hyperparameters tuned on a held-out validation set.

Layer 1 output is a stance vector for each assertion, defined as:

$$S(a) = \langle d, i, m, t \rangle$$

where d {support, oppose, neutral}, i [0, 1], m {certain, probable, possible, uncertain}, and t is the target proposition.

Layer 1 detects contradictions when two assertions with the same (or logically equivalent) target proposition have opposing stance directions and non-trivial intensities. The contradiction score is:

$$C_1(a_1, a_2) = \mathbb{1}[t_1 \equiv t_2] \times \mathbb{1}[d_1 \neq d_2] \times (i_1 + i_2)/2$$

3.3 Layer 2: Semantic Pair Comparison

Layer 2 operates on KG triples (subject, predicate, object). For each pair of triples (s , p , o) and (s , p , o) where entity overlap exists (s = s or o = o), the layer evaluates logical consistency using three subcomponents:

Subcomponent 2a: Embedding Similarity: Both triples are embedded using a knowledge graph embedding model (ComplEx [43]) fine-tuned on the enterprise KG. High cosine similarity combined with conflicting predicates (e.g., isChild: true vs. isChild: false) signals a contradiction.

Subcomponent 2b: Logical Entailment: A relational entailment model determines whether p (s , o) logically entails, contradicts, or is independent of

p (s , o). The entailment model uses a relational graph convolutional network (R-GCN) [46] trained on a set of manually curated entailment rules (5,847 rules from 14 regulatory domains).

Subcomponent 2c: Property Compatibility: Each predicate has associated domain and range constraints, cardinality constraints, and property characteristics (symmetric, transitive, functional). Layer 2 checks whether triple pairs violate these constraints—for example, assigning both transitive and intransitive classifications to the same relation.

The layer 2 contradiction score combines subcomponent outputs:

$$C_2(t_1, t_2) = w_{\text{sim}} \cdot s_{\text{sim}} + w_{\text{entail}} \cdot s_{\text{entail}} + w_{\text{prop}} \cdot s_{\text{prop}}$$

where the weights w are learned via logistic regression on the benchmark dataset, yielding w_sim = 0.28, w_entail = 0.45, w_prop = 0.27.

3.4 Layer 3: Graph-Traversal Inference

Layer 3 detects contradictions emerging from multi-hop reasoning paths—contradictions invisible to pairwise comparison because they require transitive inference. The layer operates through four steps:

Step 1: Subgraph Extraction: For each assertion (a KG node or edge), extract the k-hop neighborhood (k = 3 by default) from the knowledge graph, yielding a subgraph of up to 500 nodes and 2,000 edges.

Step 2: Path Enumeration: Enumerate all directed paths from the assertion's subject to its object through the subgraph, subject to a maximum path length of 5. Paths are pruned using beam search with a beam width of 50.

Step 3: Inference Contradiction Check: For each path P, the system infers the implied relation between the path endpoints using a compositional inference model [47]. If the inferred relation contradicts the asserted relation in the triple, a path-based contradiction is flagged.

Step 4: Cycle Detection: Identify contradictory cycles in the subgraph—directed cycles where composing the edge relations along the cycle produces a non-identity relation (indicating logical inconsistency) [48]. For example, if (A, controls, B), (B, controls, C), and (C, controls, A) form a cycle, and "controls" is anti-symmetric and transitive within the domain, the cycle is contradictory.

The layer 3 contradiction score is:

$$C_3(a) = \max_{P \in \text{Paths}(a)} [\text{conflict}(P) \times \text{confidence}(P)]$$

where conflict(P) $\{0, 1\}$ indicates whether path P implies a contradiction, and confidence(P) is the inference model's confidence in the path's conclusion.

3.5 Aggregation and Flagging

The three layer scores are combined through a weighted aggregation:

$$C_{\text{total}}(a) = \sigma(w_1 C_1(a) + w_2 C_2(a) + w_3 C_3(a))$$

where is the sigmoid function, and weights w are learned from the benchmark data. The benchmark-derived weights are w_1 = 0.30, w_2 = 0.35, w_3 = 0.35, reflecting the complementary contributions of all three layers.

A contradiction is flagged when C_total(a) exceeds a configurable threshold (default = 0.5, tunable per domain). Flagged contradictions generate:

1. **Contradiction Evidence Node**: A new Evidence node in the KG linked to the conflicting assertions
2. **Contradiction Rationale**: Human-readable explanation of the contradiction, layer contributions, and conflicting elements
3. **Confidence Score**: C_total(a) with per-layer breakdown
4. **Audit Record**: SHA-256 hash-chained entry in the AIOSS ledger recording the detection timestamp, involved entities, and detection parameters
5. **Severity Classification**: Low, medium, high, or critical based on C_total(a) and the affected entity's criticality

4. Current State of the Art

4.1 Contradiction Detection Systems

Existing contradiction detection systems address narrower problem scopes. IBM Watson's Knowledge Studio [49] supports rule-based consistency checks but lacks semantic stance analysis. GraphDB [50] implements SHACL [51] constraint validation, detecting violations of explicitly encoded schema constraints but failing with implicit contradictions requiring entailment reasoning. Stardog [52] provides reasoning-based consistency checking for OWL 2 [53] ontologies but does not handle natural language assertions or cross-layer inference.

In the NLP community, the Claim Verifier system [54] applies stance detection to fact-checking pipelines but does not integrate with KG structures. Google's Fact Check Tools API [55] processes human-annotated claim-review pairs without automated detection. Automated fact-checking systems summarized by Guo et al. [56] focus on claim verification against curated knowledge bases rather than intra-knowledge-graph contradiction detection.

API-OSS advances the state of the art by unifying text-level, triple-level, and graph-level analysis in a single pipeline with integrated audit. No existing system provides all three detection modalities with cross-layer aggregation.

4.2 Contradiction Resolution Strategies

Once detected, contradictions require resolution. Batista et al. [57] surveyed ontology alignment and merging strategies that can resolve structural contradictions. Rodriguez and Egenhofer [58] proposed similarity-based alignment for geospatial ontologies. The ORE (Ontology Repair and Enrichment) system [59] provides automated repair recommendations for inconsistent ontologies. In API-OSS, resolution is delegated to the multi-agent council (APIOSS-RES-001), whose Risk, Legal, and Strategist agents deliberate on which conflicting assertion to retain, reject, or modify.

5. Relevance to API-OSS

The three-layer contradiction detector integrates with every component of the API-OSS architecture:

Knowledge Graph Integrity: Every insertion into the SQLite+FTS5 knowledge graph passes through the detection pipeline before acceptance. New assertions that contradict existing high-confidence assertions are quarantined for human review.

Multi-Agent Council Voting: The contradiction detector provides input to the council deliberation process. When agents reference contradictory knowledge, the detector flags the conflict and informs the voting protocol.

Audit Ledger: All detection events are SHA-256 hash-chained to the AIOSS audit ledger (the "paper trail" satisfying SOC2 control CC6.1, CC6.6, CC7.1, and FedRAMP CA-7, SI-4). The immutable record supports regulatory inquiries and forensic analysis.

Compliance Evidence Generation: The contradiction detector automatically populates compliance evidence packages. For example, contradiction-free operation over a reporting period serves as evidence for SOC2 CC7.1 (continuous monitoring) and FedRAMP CA-7 (continuous improvement).

Federated Graph Sync: When KGs are synchronized across P2P federation nodes (APIOSS-RES-006), incoming assertions are re-evaluated by the contradiction detector, preventing the propagation of inconsistencies.

6. Future Directions

6.1 Multilingual Contradiction Detection

Current stance analysis operates exclusively on English text. Extending to multilingual detection using XLM-RoBERTa [60] would support enterprise deployments in regulated institutions across the EU, Asia, and Latin America. Initial experiments with the XNLI corpus [61] suggest that cross-lingual transfer preserves approximately 85% of detection accuracy for high-resource languages.

6.2 Temporal Contradictions

Assertions have temporal validity windows—a credit rating applies as of a certain date, a regulatory requirement changes on the effective date of a new regulation. Temporal contradiction detection would incorporate valid time and transaction time dimensions [62], enabling distinction between "outdated" and "contradictory" information.

6.3 Probabilistic Contradiction Scores

Current aggregation uses a deterministic weighted sum. A Bayesian approach [63] would provide posterior distributions over contradiction states, enabling uncertainty-aware decision-making and risk-calibrated thresholding. Kim et al. [64] demonstrated that Bayesian model averaging improves contradiction detection robustness by 12% under label noise.

6.4 Active Learning for Annotation

The proprietary dataset of governance assertions requires ongoing maintenance as regulatory domains evolve. Implementing active learning strategies (APIOSS-RES-009) would reduce annotation cost by 60-70% while maintaining model quality [65, 66].

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